Winning combinations:
Search strategies and innovativeness in the UK

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Abstract: **S**earching for the most rewarding sources of innovative ideas remains a key challenge in management of technological innovation. Yet little is known about which combinations of internal and external knowledge sources are triggers for innovation. Extending theories about searching for innovation, we examine the effectiveness of different combinations of knowledge sources for achieving innovative performance. We suggest that combinations involving *integrative search strategies*— combining internal and external knowledge—are the most likely to generate product and process innovation. In this context, we present the idea that cognitively distant knowledge sources are helpful for innovation only when used in conjunction with knowledge sources that are closer to the focal firm. We also find important differences between product and process innovation, with the former associated with broader searches than the latter. Using a large-scale pooled sample of UK firms, we find overall support for our conjectures, particularly in terms of product innovation.

Keywords: Innovation, openness, innovation search, knowledge integration, innovative performance.

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Introduction

The innovation process is essential to firms' performance because the ability to innovate is critical for gaining and sustaining a competitive advantage (see e.g. Nelson and Winter 1982; Dierickx and Cool 1989; Teece, Pisano, and Shuen 1997; McEvily and Chakravarthy 2002). The innovation process and how and where firms search for new and novel ideas are relatively well understood (see Bogers et al. 2017, for a review). Studies have, for instance, focused on the intra-organizational level, looking at individual-level challenges (see e.g. Dahlander, O'Mahony, and Gann 2016; Salter, Criscuolo, and Ter Wal 2014; Li et al. 2013) and organizational features (see e.g. Foss, Laursen, and Pedersen 2011; Colombo, Rabbiosi, and Reichstein 2011), or the inter-organizational level through, for instance, partnering (Laursen, Leone, and Torrisi 2010; Leone and Reichstein 2012; Leone et al. 2015). At the core of these studies is the conceptualization of innovations as the "combining (of) materials and forces differently" (Schumpeter 1912/34, : 65) and the intrinsic link between innovation and combinatorial searches. Innovation models and the view of innovation as recombination of existing bodies of knowledge have been adopted throughout the literature (e.g. Kogut and Zander 1992; Hargadon and Sutton 1997; Katila and Ahuja 2002; Fleming and Sorenson 2004; Laursen and Salter 2006; see Laursen 2012, , for an overview).

Prior studies have primarily looked at either a single source of knowledge for innovation or considered external linkages to be a homogenous source (for exceptions see Cassiman and Veugelers 2006; Grimpe and Sofka 2016; Cassiman and Valentini 2016; Olsen, Sofka, and Grimpe 2016). Little empirical research on combinatorial searches across organizational borders has distinguished between multiple sources and investigated the combinations that are more likely to precipitate innovation. In this paper, we explore the effectiveness of combinatorial searches using different sources of innovation—including internal research and development, customers, suppliers, competitors, and universities—on the probability that certain combinations will be associated with a higher probability of innovation within an organization. Previous research on the sources of innovation highlights the interactive nature of the innovation process and suggests that organizations rely heavily on their interactions with actors outside their own boundaries, including lead users, suppliers, and a range of institutions within the innovation system (von Hippel 1988; Lundvall 1992; Chesbrough 2003). Despite considerable research on the importance of particular sources (see for instance, Klevorick et al. 1995; von Hippel 2005; Tomlinson 2010; de Faria, Lima, and Santos 2010; Roper, Du, and Love 2008) and the impact of the level of external knowledge sources for innovation (see for instance, Vega-Jurado, Gutiérrez-Gracia, and Fernández-de-Lucio 2009; Grimpe and Sofka 2009; Laursen and Salter 2006; Rothaermel and Alexandre 2009; Tether and Tajar 2008; Leiponen 2012; Antonelli and Colombelli 2015), little is known regarding which combination of knowledge sources is most conducive to innovation. Given the importance of sourcing knowledge to achieve more innovation, the lack of information about "winning combinations" of sources represents a critical gap in our understanding of the innovation process. We define "winning combinations" as combinations of knowledge sources that more effectively increase the probability that firms will innovate in terms of process and/or product compared to alternative combinations.

Drawing on a knowledge-based view of firms, we suggest that integrative sourcing strategies are likely to be associated with better innovative performance than search approaches that exclusively focus on either internal or external sources. We also suggest that broad search combinations are more likely to be associated with innovation and that the use of proximate knowledge sources will facilitate effective use of more distant sources to enable innovative outcomes. In addition, building on the fundamental distinction in the literature between product and process innovation, we explore the different outcomes of combinatorial searches for each type of innovation. In this context, product innovation involves the development of new, commercialized goods and services, while process innovation involves changes to the system of production, organization, operations, and logistics for the delivery or supply of a good or service (Klepper 1997; Utterback 1994). We argue that there are important differences between product and process innovation in terms of combinatorial searches, with the former associated with broader searches than the latter. In addition, we show that the importance of suppliers is increased for process innovation, while the value of customers is increased for product innovation.

Our empirical analysis exploits data regarding over 6,790 manufacturing and service firms from two waves of the UK Innovation Survey. We explore how the use of different search strategies shapes innovativeness in subsequent years. In this context, a "search strategy" refers to any combination of knowledge sources (ranging from no sources to all sources). For product innovation, by and large, we find support for our theoretical suggestions, while the results for process innovation are ambiguous.

Our work theoretically extends the concept of combinatorial searches to include combinations of internal and external sources of knowledge, helping to deepen and extend our understanding of how organizations benefit from integrating internal and external knowledge. In this context, Rosenkopf and Nerkar (2001) address firms' internal sourcing versus inter-organizational boundary-spanning in the context of innovation, but they do not distinguish between the different types of external knowledge sources. Rothaermel and Alexandre (2009) explicitly address knowledge sourcing across organizational boundaries, including both internal and external knowledge sourcing. Although they look at the ratio of external knowledge sourcing to total knowledge sourcing, they also do not distinguish between different types of external knowledge sources. We suggest that a notion of search involving *integrative search strategies*, which include combinations of internal and external sources, would further our understanding of this phenomenon since it explicitly allows for multiple external knowledge sources.

The search for innovation

Searching for innovation can be defined as "an organization's problem-solving activities that involve the creation and recombination of technological ideas" (Katila and Ahuja 2002, : 1184). The search for new combinations of ideas often requires firms to work with many different actors outside the firm, including consultants, customers, suppliers, and universities (von Hippel 1988; Lundvall 1992). Additionally, this process can be relational or transactional (Grimpe and Sofka 2016). These searches require firms to expend considerable effort to build relationships and understandings in order to absorb knowledge from external sources (Cohen and Levinthal 1990; Lane and Lubatkin 1998) and obtain the capability to understand the routines, norms, and habits of different actors' ways of working (Brown and Duguid 2000).

A number of empirical studies assess the nature and impact of search strategies on innovation. For instance, Stuart and Podolny (1996) find that firms search in areas that are technologically close to their existing patent portfolio. Fleming and Sorenson (2004) focus on the impact of science on subsequent technological development, finding that science-based patents are often associated with increased likelihood that a firm will use new combinations in subsequent search activities. Katila and Ahuja's (2002) investigation of the impact of search depth and scope on innovative performance shows that firms can "over-search," which can lead to negative performance.

Although these studies expand our understanding of searching and its impact on innovation, they have some important limitations. First, they tend to focus on technological searches and measure them according to patent citations. Patent citations are imperfect measures of innovation searches because they focus on technology and thus may reflect both technological similarities between the focal patent and the cited patent as well as search activities. Second, by focusing on industries that obtain patents, this research offers little insight into how external search efforts shape different innovation outcomes in sectors that do not obtain many patents, such as services. Third, these studies tend to focus on single sources of knowledge (such as universities) but say little about innovation searches that involve a variety of sources of knowledge.

These limitations can be overcome by utilizing survey data to map the use of sources of innovation. Drawing on a survey of UK manufacturing firms, Laursen and Salter (2006) look at the cumulative effect of using a broad range of individual knowledge sources and suggest that there are decreasing returns when too many different sources are used. This approach has been extended by a range of studies that help to more clearly identify the advantages of external searches for firms in a broad range of countries and industries (e.g., Leiponen 2012; Leiponen and Helfat 2010; Gruber, MacMillan, and Thompson 2013; Köhler, Sofka, and Grimpe 2012; Vega-Jurado, Gutiérrez-Gracia, and Fernández-de-Lucio 2009; Lee et al. 2010). However, none of these studies investigate how these different knowledge sources are combined, relying instead on simple counts of the sources used. This means that they do not identify beneficial combinations of sources, but provide limited evidence about the different search patterns related to product and process innovation and often rely purely on cross-sectional information. The approach proposed in this paper seeks to overcome these limitations and extend our understanding of combinations of knowledge sources that promote innovative outcomes.

Hypotheses

When developing innovative ideas, firms tend to rely on what they already know and can do (Kogut and Zander 1992; Helfat 1994; Katila and Ahuja 2002). Internal knowledge is inherently very accessible, easily convertible, and well aligned to the operating routines of the organization (March 1991). In addition, local managers trust internal knowledge since it has been validated by internal processes and experience. However, focusing only on internal knowledge may lead the organization to forgo opportunities to capture external knowledge, thus hindering the effectiveness of internal projects because the solutions to problems that emerge may not be available within the organization. Thus, a “go-it-alone” approach might cause the firm to miss out on productive new combinations of internal, in-house, and external knowledge. The problem with local input sources is that they tend not to provide a variety of inspirations for resolving innovation-related problems as the local search environment may be limited in terms of opportunities for combination and recombination of knowledge (Rosenkopf and Nerkar 2001; Fleming and Sorenson 2004).

A purely external search strategy—extreme openness or a “go-all-outside” strategy—might facilitate the development of new ideas by opening up new areas of knowledge that differ significantly from a firm’s own knowledge base (March 1991). These external sources may provide skills and competencies that are far removed from the firm’s current practice and products and may provide opportunities to learn from the users and developers of technologies that are new to the firm (von Hippel 2005). Some firms may be attracted to the low cost and potentially high rewards associated with new open models of innovation (Chesbrough 2003). This attraction is driven by the belief that external sources will be effective substitutions for internal investments and enable firms to “outsource” the innovation process (Rigby and Cook 2002). However, this “go-all-outside” approach could lead to a lack of integration between the firm’s internal efforts and external sources, causing the knowledge obtained and ideas developed from these outside sources to be poorly utilized if they are too distant from and discordant with the organization’s internal knowledge and capabilities. External sources may offer the allure of novelty, but this novelty will only be valuable if it can be integrated successfully into the firm’s knowledge base.

The knowledge-based view of firms stresses that a firm's primary task is to integrate specialized knowledge inputs (Grant 1996b). Knowledge integration is achieved through mechanisms such as setting rules, creating a common language, generating routines for integration, and learning to enable effective interactions between specialists performing non-standardized, complex tasks (Grant 1996a, : 12-14). Thus, the firm must develop high-level routines for synthesizing different inputs from inside and outside the firm to achieve overall performance or output that is more than the sum of its parts. Drawing on this logic, we suggest that those firms that combine internal and external searches are likely to exhibit higher performance than firms whose searches are either only internal or only external. We call a strategy that combines internal and external searches an *integrative search strategy.* Firms that adopt such a strategy are likely to have higher success rates in process and product innovation. Accordingly, the external and internal knowledge being combined should be complementary (i.e. mutually reinforcing, see, Arora and Gambardella 1990; Cassiman and Veugelers 2006), help to optimize internal search efforts by providing insights and resources that are not available internally, and increase the effectiveness of external searches by directing search efforts towards the most productive sources. Based on this background, we developed the following hypothesis:

> *H1. Firms that engage in integrative search strategies are more likely to be innovative than firms that rely on only external or internal sources.*

The literature on combinatorial search for innovation suggests that firms that are able to harness diverse sources of knowledge are more likely to develop and commercialize new ideas. Developing an innovative idea may require firms to combine knowledge from a range of different internal and external sources, and by recombining this knowledge, firms will be able to see opportunities to reuse their existing knowledge in new ways and combine it with new knowledge (Hargadon and Sutton 1997; Laursen and Salter 2006).[1] This process of recombination often involves brokering knowledge from domains where it is common to those where it is novel (Burt 2004). Brokering requires that a firm is aware of the opportunities afforded by recombination. Drawing from a diverse range of sources is a strong signal that a firm has developed the "bandwidth" required to exploit diverse opportunities in its external environment. Therefore, search strategies that seek to recombine complementary knowledge from a broad range of sources[2] are likely to result in greater opportunities for innovation than narrower search strategies. Thus, we developed the following hypothesis:

H2. Firms that use broad integrative search strategies are more likely to be innovative than firms with narrow search strategies.

Not all types of knowledge sources for innovation are equally easy to exploit; some sources are more cognitively distant from the focal firm. We follow Nooteboom et al. (2007, : 1017) in viewing cognitive distance between organizations as differences in "systems of shared meanings…established by means of shared fundamental categories of perception, interpretation and evaluation inculcated by organizational culture." Here, we suggest that the cognitive distance of an external source is, in part, a function of whether the type of organization associated with the source of innovation has economic interests and incentive systems that are aligned with those of the focal firm. When these interests and incentives are aligned, it is easier for the focal firm to collaborate with the external source since the former

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[1] Laursen and Salter argues that the firms that invest in broader external search "…may have a greater ability to adapt to change and therefore to innovate." It does not, however, allow for the possibility of using integrative search strategies involving both internal and external sources of knowledge to achieve innovation.

[2] In the empirical part of the paper, we work with a total of five knowledge sources. In this context, we consider a strategy consisting of at least three sources to be "broad."

will be exposed to less risk and lower coordination costs. Figure 1 summarizes our arguments regarding cognitive distance from the focal firm (in terms of economic interests and incentives) for different sources of innovation and knowledge.

<Insert Figure 1 about here>

Nooteboom (1999, : 5-6) argues that, generally, vertical relationships are likely to be more successful than horizontal relationships because there is lower risk of misaligned interests and incentives. Horizontal relationships are likely to be zero-sum games in which the participants try to capture each other's market share, which carries a potential risk of defection. Vertical relationships involving suppliers and/or customers most often involve common interests and incentives; the more downstream products are sold, the more both parties will benefit. Universities also often interact with firms due to aligned economic interests, even though they operate under a different incentive system that rewards disclosure rather than exploitation of knowledge (Dasgupta and David 1994; D'este and Patel 2007; Roach and Sauermann 2010; Köhler, Sofka, and Grimpe 2012; Agarwal and Ohyama 2013). This fundamental difference makes universities a cognitively distant source of innovation for firms.

The ability to integrate insights, ideas, and bodies of knowledge from these sources, each of which is associated with a different degree of cognitive distance from the focal firm, is crucial for effective use of any source or combination of sources. Building on this idea, we argue that firms that use an integrative search strategy involving cognitively proximate external knowledge sources will be more likely to benefit from more distant sources of knowledge. In other words, working with (a combination of) closer knowledge sources allows a firm to more effectively span more distant boundaries. Certainly, the central problem with using distant external knowledge sources lies in the fact that this knowledge is unlikely to fit the pre-existing categories and ways of working in the focal firm (Cohen and Levinthal

1990; Lane and Lubatkin 1998). In other words, because external knowledge is developed in a different organizational context, it is "sticky," or difficult to utilize in another context (von Hippel 1998). However, when firms seek to actively align internal and familiar external knowledge, they are better able to recognize opportunities to use distant external knowledge in new settings (Hargadon and Sutton 1997). Combining internal knowledge with proximate external knowledge helps firms more effectively re-package and translate external knowledge from distant sources. For instance, if proximate knowledge (from internal sources, suppliers, or customers) is not included in a combination of knowledge sources, it is very difficult for a focal firm to find uses for (distant) knowledge from universities and competitors in its innovation process. Fundamentally, these more familiar knowledge sources (internal, suppliers, customers) can assist the focal firm to find applications for the more distant knowledge (held by universities and to some extent by competitors). Likewise, knowledge from competitors may be difficult to integrate into the focal firm's own innovation projects because firms do not desire to disclose all aspects of the relevant knowledge. In such cases, internal and proximate external sources can help fill the gaps in knowledge obtained from competitors so that it can be productively employed in the innovation process of the focal firm. Certainly, a firm can turn to its suppliers to help it copy its competitors' ideas for products as their suppliers may directly provide machinery, components, or materials to competitors or be in a position to develop similar machinery, components, or materials for the focal firm. For example, when Apple worked with Corning to help develop Gorilla Glass, a durable, scratch-resistant cover glass for the iPhone, its competitors—HTC, Samsung, and Nokia—later utilized this same product. Based on this, we developed the following hypothesis:

H3. Firms that use cognitively distant knowledge sources are more likely to innovate if they apply an integrative search strategy that involves cognitively proximate external knowledge sources.

Studies of innovation commonly highlight the differences between product and process innovation (Tushman and Anderson 1986; Utterback 1994). Product innovation involves the creation of technologically new products, while process innovation results in new elements that alter an organization's operations and production processes—the flow of materials and tasks regarding information management and capital equipment—in order to lower costs and/or ensure better product quality (Utterback 1994; Freeman and Soete 1997; Rosenberg 1976). Product innovations often arise out of interactions with lead users, universities, and other key sources of innovation (von Hippel 1988; Laursen and Salter 2006; Köhler, Sofka, and Grimpe 2012). Product innovation requires extensive interaction and the orchestration of many different internal and external sources of knowledge (Brown and Eisenhardt 1995). This, in turn, requires that product innovators have strong "combinative capabilities" to integrate different bodies of knowledge from different sources (Kogut and Zander 1992; Grant 1996a; Nickerson and Zenger 2004).

Process innovation, on the other hand, has a strong focus on internal processes and efficiency, indicating that it arises out of local searches. Process innovation is described by Tushman and Rosenkopf (1992, : 313) as "the most primitive form of innovation," This description may reduce the importance of process innovation; several researchers have demonstrated its relevance to business performance (e.g. Parisi, Schiantarelli, and Sembenelli 2006). Nevertheless, as Rosenberg (1982) suggests, process innovation tends to be "grubby and pedestrian," occurring silently within a firm through learning-by-using and learning-by-doing. As such, process innovation often involves a high level of tacitness since it is associated with subtle changes to operating routines that are hard to observe and difficult for the firm and others to codify. Process innovations tend to be determined by managerial decisions about how to best organize the firm in order to maximize the efficiency and effectiveness of internal procedures, routines, and operations (Tomlinson 2010; He and Wong 2004; Reichstein and Salter 2006). Process innovation, therefore, is simpler, more local, and requires fewer external searches than product innovation. Thus, we developed the following hypothesis:

> *H4. Process innovation is likely to be associated with integrative search strategies that involve fewer knowledge sources than those associated with product innovation.*

Suppliers' role in shaping process innovation is widely acknowledged (Pavitt 1984; von Hippel 1988). Process innovations often require manufacturers to work closely with suppliers of specialized machinery. For example, the implementation of lean production often requires firms to develop new relationships with suppliers and draw on them for knowledge about production and delivery times (Womack, Jones, and Roos 1990) or new types or combinations of technologies. Suppliers themselves can also spur process innovation, as new components and technologies may allow user firms to reshape their production processes. Indeed, there is a strong relationship between technologies and components available from external suppliers and the potential for firms to achieve process innovation.

As mentioned earlier, newer models of innovation highlight the critical role of users (including customers) in shaping firms' potential for product innovations. Von Hippel (2005; 2001) describes the central importance of users when drawing out new products from manufacturers since users may provide a rich tapestry of experience and ideas about how to improve existing products and may even spur the creation of new products. In many cases, users are the first to experience the need for a new product, and thus they may be incentivized to contribute their knowledge and experience as they will often be the first to benefit from a product innovation (von Hippel 1988). Based on this discussion, we present the following hypotheses:

Hypothesis 5a: Process innovation is associated with search strategies that involve drawing knowledge from suppliers.

Hypothesis 5b: Product innovation is associated with search strategies that involve drawing knowledge from customers.

Data and Method

Data and Sample

The goal of our empirical analysis is to determine which combinations of knowledge sources are more associated with a higher likelihood that a firm will achieve product or process innovation. To do this, we use data from two consecutive UK Innovation Surveys conducted in 2005 and 2007. The data for our dependent variables were obtained from the 2007 survey and the data for our independent and control variables were obtained from the 2005 survey. Using different data sources for the dependent and independent variables allows us to avoid common-method bias.

The UK Innovation Surveys were carried out by the Office of National Statistics (ONS) on behalf of the Department for Business, Innovation and Skills (formerly the Department of Trade and Industry, or DTI). The UK Innovation Survey is part of the fourth Europe-wide Community Innovation Survey (CIS) (Robson and Ortmans 2006). The implementation of these surveys, the types of questions included in the surveys, and the sampling techniques used follow the guidelines described in the Organisation for Economic Co-operation and Development's (OECD) Oslo Manual. The CISs are often described as "subject-oriented" because they focus on innovating agents rather than technology (Archibugi and Pianta 1996). Data from these surveys may provide a useful complement to traditional measures of innovation output, such as patent statistics (Cassiman and Veugelers 2006; Leiponen and Helfat 2011; Mairesse and Mohnen 2002), because they cover a wider range of industries, including services, and different types of innovative outputs, such as product and process innovation (Leiponen and Helfat 2010).

The UK Innovation Surveys cover many different aspects of the innovation process. Firms are asked to report whether they have achieved product and/or process innovation in the preceding years. Product innovation is defined as "the market introduction of a new good or service or a significantly improved good or service with respect to its capabilities, such as quality, user friendliness, software or subsystems," and process innovation is defined as "the use of new or significantly improved methods for the production or supply of goods and services" (DTI 2005). The surveys include questions about other innovation-related activities such as identifying sources of information that are relevant to innovation and spending for research and development (R&D). The validity of the CIS questionnaire was established through a series of pilot studies and pre-testing before its implementation in different European countries and a number of industries, including manufacturing, services, and construction (Smith 2005).

The fourth UK Innovation Survey was distributed in 2005 to a sample of 28,000 firms with 10 or more employees in the manufacturing and services sectors.[3] The survey respondents were generally managing directors, chief financial officers, and R&D managers. A total of 16,240 firms took part in the survey, corresponding to a response rate of 58

[3] The survey was administered at the reporting unit level, with a reporting unit defined as "the smallest combinations of legal units which have a certain degree of autonomy within an enterprise group." Thus, a reporting unit can be assumed to be a firm, which may have more than one business establishment (e.g., a plant) and can be part of a larger multi-enterprise business entity (i.e., a group).

percent. This high response rate greatly reduces the potential for non-response bias (Armstrong and Overton 1977, : 396). The sample of firms was determined by the ONS based on a random sampling of firms with fewer than 250 employees stratified across 23 sectors, 12 regions, and various size bands. All firms with more than 250 employees were included in the sample. The fifth UK Innovation Survey was sent to 28,000 firms in 2007—the same set of firms that received the survey in 2005—and achieved a response rate of 53 percent. Because the sample population was the same for both surveys, when we matched firms using unique identifiers in the fourth survey with information about those firms in the fifth survey, we achieved a large overlap sample (6,792 firms) that responded to both surveys.

Although the size of the matched sample is relatively large, there is still the possibility that the data used in our analysis suffered from selection bias. We checked for this by testing whether the distribution of the main characteristics of firms affecting their innovative performance (e.g., size, age, R&D intensity, technological cooperation, use of government funding to support R&D investment, and participation in a wider corporate group) differed between the firms that replied to both surveys and those that responded only to the 2005 survey. There were no statistically significant differences between the two groups for most variables except age. The average age of firms in the overlap sample was 21.7 years, compared with 19.8 years for those firms that did not respond to the fifth survey. This finding might be explained by survival bias. However, the correlation between age and our main independent variables, search strategies, is very low, which suggests that although the two samples differ in terms of firm age, there are not necessarily differences regarding the independent variables of interest in this study. In addition, we matched the innovation survey data to the ONS Inter-Departmental Business Register to obtain information about firms' age and ownership.

Measuring the impact of different search strategies

To assess the effect of different search strategies on firms' performance, we follow an approach similar to those used in the literature to measure complementarities (Ennen and Richter 2010). In particular, we adopt a system approach (for an application of this approach, see, e.g., Ichniowski, Shaw, and Prennushi 1997), which derives the relative performance outcomes of an entire set of variables (26 in our case) through regression analysis. Even through this approach is not a formal test of complementarity, we prefer it to the interaction approach, since the latter tests for the presence of complementarity among only a few variables (typically, two; (e.g., Cassiman and Veugelers 2006).

Measures

Dependent variables. We use three measures of innovative performance: one referring to product innovation, one to process innovation, and one to the share of sales of innovative products. *Product innovation* is measured using an item from the fifth UK Innovation Survey, which asks firms whether, from 2004 to 2006, they introduced a technologically new or significantly improved product (good or service). *Process innovation* is measured in a similar way, with an item in the questionnaire asking whether firms have used any new or significantly improved technology for the production or supply of products (goods or services) from 2004 to 2006. These variables are equal to 1 if the firm introduced a new product or a new process and 0 otherwise. *The share of sales of innovative products* are measured by three items in the questionnaire, which asked firms to report the percentage of total turnover attributable to products introduced from 2004 to 2006 that were *new to the market*, *new to the firm*, and *significantly improved*. We use the sum of these three percentages to determine the returns of product innovations.

Our measures of product and process innovation are similar to those used in a number of other studies, such as those of Reichstein and Salter (2006), Love et al. (2009), and Leiponen and Helfat (2010), and Foss et al. (2011). Our share of innovative sales measure is also consistent with prior studies (Mairesse and Mohnen 2002; He and Wong 2004; Cassiman and Veugelers 2006; Laursen and Salter 2006). These measures allow researchers to explore innovative outcomes across the entire economy, unlike conventional indicators of innovation such as citation-weighted patents, which may be relevant only to a small number of sectors. Moreover, there is a large body of research showing that these measures have strong predictive validity for explaining a variety of organizational outcomes, including growth in productivity, sales and employment growth, survival, profits, and the ability to obtain credit from financial institutions (recent examples include, Love, Roper, and Du 2009; Cefis and Marsili 2005; Evangelista and Vezzani 2010).

However, these measures have several important limitations. First, they are self-reported, and thus we cannot be sure that statements about innovative achievement are objectively true. Although the survey provides some definitions, managers may interpret the information differently based on their organization's setting and history. Second, since the data are confidential, it is not possible to validate the responses with more "objective" measures, such as patents. Third, our binary measure of innovativeness does not allow us to discriminate between firms that have introduced only one product or process innovation from those that have introduced many during the same period. However, our measure examining the share of sales from innovative products helps to alleviate this shortcoming as it assesses the overall commercial success of a firm's product innovations.

Independent variables. Search strategies that combine sources of knowledge are measured using responses to the fourth UK Innovation Survey, which covers the period from 2002 to 2004. Respondents were asked to assess on a four-point scale (1="Not Used"; 2="Low"; 3="Medium"; 4="High") the importance of five sources of knowledge for the firm's innovative activities: internal sources, suppliers and consultants, customers, competitors, and universities and other research institutes. These knowledge sources broadly correspond to the resources and institutions that are considered to be part of the national innovation system (Lundvall 1992). This definition has been used in several other empirical studies (e.g., Laursen and Salter 2006; Leiponen and Helfat 2010; Grimpe and Sofka 2009; Leiponen and Helfat 2011).

The responses to the questions are converted into binary variables: 1 if the source is of medium or high importance and 0 if the firm does not use the source or evaluates it as low. This means that our search strategy, called “internal only,” identifies those firms that rate internal sources as having medium or high importance and either do not use any other sources of knowledge or consider them to be of low importance for their innovative activities. This produces 32 (2^5) possible innovation search strategies characterized by some combination of external and internal sources of knowledge. To ensure the reliability of the econometric estimations, we consider only strategies adopted by 12 or more firms since the inclusion of less common strategies implies reliance on only a few observations, which could lead to a breakdown of the parameter estimates (Mili and Coakley 1996). This reduces the number of examined strategies to 26. Table 1 displays the different search strategies and the number of firms that adopted them.

Although these search measures allow us to measure the use of different knowledge sources, they provide only indirect and partial evidence of the depth of searches in each of these domains. In particular, our measure of internal sources is based on a single item and does not cover the range of internal sources available to the firm, such as marketing, R&D, and senior management. Moreover, similar to many other semantic scales, respondents may interpret terms such as “use” of a source differently, and without a clear definition of “use,” it is difficult to know the level of use to which the respondent is referring in his or her response. Also, it is not possible from the survey to identify whether a firm draws on single or multiple partners in its use of an individual source, nor to assess the degree of overlap or past collaboration between the firm and its sources. Despite these limitations, the survey item does provide information on the broad range of sources available in the innovation system and therefore is fairly comprehensive in its coverage of the main sources of knowledge for innovation.

Control variables. We control for firm size and whether the firm engages in R&D since these variables often influence innovation performance (Cohen 1995). *Firm size* is measured as the number of employees and their full-time equivalents (expressed in logarithms) in 2004. The extent of the firm's R&D efforts is determined by two items in the survey: *R&D active*, which is equal to 1 if the firm undertakes activities aimed at increasing the stock of knowledge and using it to create new or improved products or services from 2002 to 2004. We also control for the human capital of the firm by introducing a measure, *share of scientists and engineers*, which is defined as the proportion of scientists and engineers to the total number of employees in 2004. Another important firm characteristic that may be correlated with innovative performance is age. We use data from the Inter-Departmental Business Register, which covers all UK businesses registered for value-added tax purposes, to measure *firm age* in years. We include a dummy variable representing whether the firm is part of a larger organizational group (*part of a group*), which is equal to 1 if the firm belongs to an enterprise group, and a dummy representing whether the firm is domestically owned (*domestic*) using data from the Inter-Departmental Business Register. We introduce a variable to control for the size of the perceived product market (*market focus*). This is measured using a 4-item scale based on a question asking firms to indicate which of four markets (local, national, European, or beyond Europe) they perceive to be the largest for their products. This variable controls for the possibility that firms operating in the international market tend to be more innovative.

We include a binary variable measuring *innovation co-operation* that controls for whether or not firms engaged in cooperative R&D with other firms or institutions. Previous studies have found a relationship between cooperation and innovative performance (e.g., Powell, Koput, and Smith-Doerr 1996). Although we control for a number of factors that could predict the innovative performance of companies, we added a dummy variable (*active innovation*) that is equal to 1 if the company was actively innovating during the period from 2002 to 2004. This dummy is also equal to 1 if a firm introduced a new or significantly improved good, service, or process; was engaged in innovation projects that were unfinished or abandoned at the time of the survey; was engaged in longer-term innovation activity such as basic R&D; had expenditure in areas such as internal R&D, training, and acquisition of external knowledge or machinery and equipment linked to innovation activities; or had formally cooperated on innovation activities with other enterprises or institutions. The inclusion of this control helps to ensure that our results are not affected if some firms do not innovate because it is not part of their corporate strategy. This variable is intended to capture serial correlation between innovative activities and at least partially capture unobserved factors that drive innovative conduct among firms. We expect some hysteresis in firms' innovativeness to lead to a positive parameter estimation for this variable. We also introduced another dummy variable (*prior innovations*) that is equal to 1 if the firm did not need to be involved in any innovation activities from 2004 to 2006 because of successful prior innovations.

Literature on publicly funded R&D (Griliches 1995) suggests that government support for R&D in the form of tax credits, deductions, grants, or low-interest loans, which increase investment, can have a positive and significant effect on firms' innovative performance. We account for this by including a dummy variable (*government funding*) that is equal to 1 if the firm received public financial support for innovation from a regional, national, or European source during the period from 2002 to 2004. Finally, we include seven 1-digit SIC-92 industry dummies to account for differences in the propensity to innovate across industries (Klevorick et al. 1995).

Econometric method

The analysis relies on three dependent variables. The first two are binary variables representing the incidence of product and process innovation. Since prior research has indicated that these two types of innovation are often mutually independent (Reichstein and Salter 2006), we use a bivariate probit specification, which is a joint model of two binary outcomes. This model was also applied in the context of product and process innovation by Hall, Lotti, and Mairesse (2009). This model may generally be specified as follows:

$$y_1=a_1+b_1x_1+u_1$$

$$y_2=a_2+b_2x_2+u_2$$

where y_1 and y_2 refer to product and process innovation, respectively; a_1 and a_2 represent the intercept terms of the two equations, respectively; b_1 and b_2 are the vectors of the estimated parameters; x_1 and x_2 are the vectors of explanatory and control variables, respectively; and u_1 and u_2 are the two estimated error terms, respectively. In this paper, we consider a case in which x_1 and x_2 contain the same sets of explanatory and control variables. It is important to note that even if the two sets of variables in x are the same, we cannot assume that b_1 and b_2 are equal as well. If product (y_1) and process (y_2) innovation are independent from each other, the error terms (u_1 and u_2) become uncorrelated ($\rho=0$) and the two equations boil down into two separate probit models. If the two types of innovation are correlated ($\rho\neq0$), the estimated probabilities become a function of the joint estimated parameters of the two equations. The correlations between the error terms need not be due to their complementarity; they may appear due to the influence of common unobservable factors.

To test the robustness of the results with regard to product innovation, we employed a third dependent variable, *share of sales from product innovation*. This measure has been utilized by many other studies using similar data (see e.g., Cassiman and Veugelers 2006; He and Wong 2004; Mairesse and Mohnen 2002; Laursen and Salter 2006). This measure overcomes some of the shortfalls of binary measures of product innovation and acts a robustness check for our bivariate probit results. For this dependent variable, we use a tobit specification since the share of sales from innovations is significantly skewed to the right and is truncated at 0 and 100.

Results

Descriptive Statistics

Table 1 contains some descriptive statistics and shows the distribution of the search strategies. Although the most popular strategy is to not engage in any search activities, with 1,977 firms opting for this approach (29.0 percent), we find that many firms search broadly and combine internal and external sources of knowledge. Indeed, these combinatorial search strategies are much more common than strategies involving only internal or only external sources of knowledge. It is interesting to note that strategies relying on only one source of knowledge are less popular than strategies relying on multiple sources, which suggests that most firms seek to combine knowledge from a range of sources. The most popular search strategy involves internal sources, suppliers, customers, and competitors (1,255 firms; 18.5 percent), while the least-used strategy is sourcing knowledge from only suppliers and universities (12 firms; 0.2 percent).

Looking at the descriptive statistics of the dependent variables, 15.0 percent of the firms engage in process innovation and 24.5 percent engage in product innovation. The average share of sales from innovative products is 7.4 percent. Regarding the control variables, more than a third of the firms are part of a wider corporate group and a similar proportion are foreign-owned. From 2002 to 2004, more than a quarter of firms invested in R&D, and 14.8 percent engaged in innovative collaborative agreements.

Given space limitations, we do not report the full correlation in Table 1.[4] However, the table clearly shows that the tetrachoric correlation between the innovation dummies is 0.71, which indicates that the bivariate probit may be the right choice for the multivariate analysis. The other correlation estimates tend to be very low, suggesting that there is little reason for concern regarding multicollinearity. This was confirmed by a variance inflation factor (VIF) analysis, which resulted in VIFs below 4.5.

<Insert Table 1 about here>

Regression results

Table 2 shows the coefficient estimates of the bivariate probit. Before commenting on the results, note that the estimated correlation coefficient of the error terms is always positive and significant, indicating that product and process innovations are influenced by a common unobservable factor and that it is important to simultaneously model product and process innovation outcomes. Thus, the bivariate model appears to be a highly appropriate estimation method.

<Insert Table 2 about here>

The first two columns in Table 2 show the estimates of our baseline model, which includes only the control variables. The coefficients of this model are consistent with the findings of previous innovation literature and, more importantly, do not vary much in magnitude or significance when we include our main independent variables.

[4] These are available upon request.

The last two columns in Table 2 report the results of the full model. To assess the magnitude of the coefficient estimates, we calculate the marginal predicted probability of achieving a product (or process) innovation using the bivariate probit estimations, with all other independent variables set at their means. Table 3 reports these predicted probabilities. For example, firms drawing on internal sources, customers, and universities are 22.6 percent more likely to engage in product innovation compared to companies not engaging in search activities. Similarly, we found that firms that use suppliers and universities as sources of knowledge are 16.5 percent more likely also to engage in process innovation than companies not engaging in search activities.

<Insert Table 3 about here>

In a similar fashion, we ran tobit regressions against the share of sales from innovations. These results are presented in Table 4. The overall results are comparable to those of the product innovation equation in the bivariate probit regression in terms of control variables. The search strategy variables also exhibit substantial overlap in patterns of significance, providing some support for our initial regression results.

<Insert Table 4 about here>

To identify the best strategies for each of the innovation outcomes, we test each coefficient estimate against the others. The results of these Wald tests regarding product innovation, process innovation, and share of sales from product innovation are reported as matrices in Tables 5, 6, and 7, respectively. The tables also contain the estimated coefficients of each strategy. Stars in the cells indicate significant differences between the strategies in the corresponding column and row at different levels of significance. To simplify the interpretation of our findings, we report only the results of a significant Wald test when the coefficient in the row is greater than the coefficient in the corresponding column. This should help to identify winning strategies (i.e., those having a significantly more pronounced association with product or process innovation). Cells without stars therefore indicate that the two strategies being compared do not have significantly different associations with innovation outcomes or that the coefficient estimate of the strategy in the column is statistically significantly smaller than the coefficient of the strategy in the row.

The results of the Wald tests confirm that the search strategy including internal sources, customers, and universities (strategy 21) has a pronounced association with product innovation (see Table 5). Strategies 22, 23, and 25 exhibit equally strong associations with the likelihood of introducing a product innovation and display even higher coefficients. All of these strategies involve suppliers and competitors, suppliers and universities, and competitors and universities, respectively, as well as customers and internal sources. Our results suggest that strategies employing only one knowledge source, whether external or internal to the firm, are less likely to be associated with successful innovation, indicating that combinatorial strategies outperform single-source approaches.[5] In general, the findings suggest that combinations involving both internal and external knowledge sources are more likely to lead to product innovation than strategies that use only external sources of knowledge. Indeed, the results regarding product innovation are consistent with Hypothesis 1, indicating that integrative search strategies are advantageous for innovation. Regarding process innovation (see Table 6), the results are less clear since firms using strategies 16 and 19—which involve internal sources—do not perform better than several strategies (7, 8, 11, and 12) that do not involve internal sources. Thus, while process innovation requires combinatorial searches, it seems unnecessary to combine external and internal sources.

[5] We tested the equality of the coefficients for all strategies using only one search channel and found that we cannot reject the null hypothesis (*p*-value=0.603). In other words, they all have the same effect in terms of likelihood of product innovation. The results regarding the equality of coefficients for strategies involving only one or two search strategies were similar (*p*-value=0.254).

<Insert Table 5 about here>

<Insert Table 6 about here>

<Insert Table 7 about here>

Overall, the findings regarding product innovation support Hypothesis 2 as they suggest that, on average, broad combinatorial strategies are associated with better outcomes than narrow strategies for both product and process innovation. Again, the results are less clear regarding process innovation (see Table 5) in Hypothesis 2. Three of the best-performing strategies (7, 8, and 12) do not include internal sources, and two include only two sources (7 and 8). Overall, our results regarding process innovation do not support Hypothesis 2.

Hypothesis 3 states that firms that use cognitively distant knowledge sources will be more likely to innovate if they use an integrative search strategy involving external knowledge sources that are cognitively proximate. For product innovation (see Table 5), we find evidence supporting this hypothesis since the most cognitively distant sources (or search channels), competitors and/or universities, exhibit significantly larger coefficients than other strategies only when combined with internal sources and at least one other external source that is cognitively closer to the focal firm. As previously mentioned, strategy 21 displays the highest coefficients of the 26 strategies investigated. It involves internal and cognitively close (customers and suppliers) sources as well as a cognitively distant (universities) source. The strategy using only universities (strategy 5) is associated with by far the lowest coefficient regarding the likelihood of introducing new innovations, confirming Hypothesis 2. Again, the picture is less clear for process innovation (see Table 6), yet there is some evidence to support Hypothesis 2. Strategy 5 (universities only) is ranked significantly lower than 20 other strategies, and strategy 3 (suppliers only) is ranked lower than 15 other strategies. In general, combinatorial strategies that include universities do not tend to be associated with high levels of process innovation. While somewhat weak, these findings do provide some evidence in favor of Hypothesis 3. We nevertheless have to conclude that, in the case of process innovation, the hypothesis is only partially supported.

Hypothesis 4 is concerned with differences in the importance of broad combinatorial searches for product and process innovation. The results provide partial support for this view; the strategies associated with the highest likelihood of product innovation are broad, but for process innovation, narrow search strategies do not seem to be associated with lower likelihood of innovation than broad strategies. In fact, in the process innovation regression, some of the strategies involving only two sources (7 and 8) were equally ranked with strategies that involve multiple sources (16 and 19). This suggests that process innovation may require less combinatorial novelty because it involves more modest types of innovative achievement.[6] However, it is also clear that some of the strategies associated with the highest likelihood of process innovation involve a range of sources (in particular, strategies 12 and 23). Given this, our results are not definitive.

Consistent with Hypothesis 5a, we find that suppliers as a source of knowledge increase the likelihood that a firm also is engaged in process innovation as almost all of the winning strategies include this source (7, 8, 12, 13, 22, and 23). In line with Hypothesis 5b, for product innovation, customers are most often part of a winning combination; customers are involved in all of the highest-ranked strategies (17, 20, 21, 22, 23, 25, and 26).

Table 7 presents the corresponding comparisons using the results of the tobit regression as inputs. These results generally confirm the results of the bivariate probit analysis for product innovation. Yet, there are some discrepancies between Tables 5 and 7. For instance, strategies

[6] This is confirmed by the fact that when we test whether all the coefficients of search strategies employing one or two sources are the same using only one search channel, we can reject the null hypothesis (*p*-value=0).

7 and 8 are highly associated with firms with a high share of sales from product innovations, even if they involve only two sources of knowledge.

As a robustness check, we re-ran all our models using a higher threshold (50 firms per strategy group), and reducing the number of strategies to 15 (by excluding 4, 5, 7, 8, 11, 12, 15, 16, 19, 21, 24, and 25). The results of this robustness check are consistent with the results reported above. We also re-estimated the models using a standard probit estimation procedure, the results of which are consistent with those obtained using the more appropriate bivariate probit model. To check the robustness of our tobit model estimations, we exclude those firms that did not actively engage in innovation from 2002 to 2004. This excluded 2,358 firms from the analysis. Again, the results are consistent with those reported in Tables 4 and 7. We also tested whether the results are robust to the exclusion of the share of innovative sales that firms have attributed to the launch of significantly improved products. Also, in this case, we found that the coefficients' estimates are consistent with those presented in Tables 4 and 7.

Discussion and conclusion

By bringing together arguments regarding the benefits of combinatorial searches in the distributed innovation literature, we aimed to cast new light on which combinations of knowledge sources provide the greatest opportunities for subsequent innovation. We have tried to advance understanding about the nature and type of external sources that shape innovative outcomes by extending knowledge about the utility of sources of innovation. In general, the results are consistent with our expectations, especially for product innovation. The results for process innovation are more ambiguous. In the context of product innovation, we found clear evidence of the importance of adopting strategies involving integrative search combinations. These results demonstrate that sources of innovation should be viewed as a mutually reinforcing system and that it could be risky for firms to rely on a single source or a small number of internal or external knowledge sources to spur innovation. Indeed, the "go-it-alone" strategy of using only internal sources and the "go-all-outside" strategy of using only external sources are generally less effective than using a strategy that combines internal and external knowledge.

Apart from the cognitive problems associated with an effective combinatorial search process, type of innovation appears to predetermine which combination will provide the highest payoff. This paper shows that the strength of association with innovation performance of different search combinations are contingent on the type of innovation being considered. In this regard, we found important differences between product and process innovation. In general, process innovation appears to require narrower searches than product innovation. This suggests that process innovations requires less combinatorial novelty than product innovation and therefore that process innovation may be a less complex form of innovation in terms of knowledge sources. This is not to say that process innovation is straightforward or simple; it may involve significant organizational change.

We contribute to the literature on open and distributed innovation. In this context, we can confirm the importance of users—especially for product innovation—as suggested by previous research on the innovation process (see for instance, Urban and von Hippel 1988; Bogers, Afuah, and Bastian 2010). Customers as a source of knowledge were always included in our winning combinations. The literature on user innovation tends to focus on the importance of users for stimulating innovation, but our findings point to the limitations of using single sources of innovation. This leads to a more general contribution: rather than assessing the effects of a specific knowledge source for innovation, which is common in the distributed innovation literature, the present study analyzes the impact of particular *combinations* of knowledge sources.

We also contribute to the literature on knowledge integration and innovation. We extend the strand of research that addresses inter-organizational aspects by explicitly accounting for the fact that external knowledge sources are heterogeneous. It is not just a question of how much external knowledge the firm can exploit in its innovation processes; we must also consider the type of knowledge being used and how it is combined with other types of knowledge. In this context, we believe that our notion of an integrative search strategy may be useful. We also show that searches aimed at cognitively distant knowledge sources are only helpful for product innovation when used in conjunction with knowledge sources that are closer to the focal firm. This is an important addition to the literature that considers organizational boundary-spanning to be a dichotomous variable (Rothaermel and Alexandre 2009; Rosenkopf and Nerkar 2001).

Our paper has some implications for management. First, it is dangerous for managers to use “go-it-alone” or “go-all-outside” approaches when pursuing innovation. Second, it is important for managers to try to develop integrative search strategies that combine internal and external sources of knowledge, particularly for product innovation. They need also to develop routines to assimilate and synthesize the specific skills and competencies of different sources. Third, we found that, for product innovation to benefit from distant sources of knowledge, it is useful for the firm to combine this knowledge with the ideas and experiences of more proximate sources, such as customers and suppliers. This suggests that using proximate sources of knowledge may spur more successful, distant search efforts.

Limitations and directions for future research

Analysis of the implications of combining complementary sources of knowledge for innovation is complicated and requires one to simplify assumptions in order to make the analysis tractable. As a result, the results of this paper should be interpreted cautiously. The present study was limited to exploring search strategies, and although we include a measure of the use of internal sources, it is somewhat rough and does not tell us much about the ways in which external sources of knowledge are integrated into internal innovation practices (Foss, Laursen, and Pedersen 2011). A second limitation of this study is related to possibility of overemphasizing the dependent variable, the distinction between innovators and non-innovators. It does not reveal anything about the amount of projects developed, it does not consider their scale, and it does not consider the rate of successful innovation projects. However, although our dependent variable is simple, our findings regarding the ratio of sales of new products to total sales did produce results that are reasonably consistent with the results pertaining to the distinction between innovators and non-innovators. Third, also pertaining to the dependent variable, many firms may survive on past innovations or may be able and willing to innovate in the future. Although our lagged structure to measure innovativeness and searches and our use of a control for prior innovation may mitigate this concern, it is not fully addressed. Fourth, by comparing the performance of the most common search strategies, we overlook less common combinations that may be highly advantageous for innovative performance. Thus, this study identifies winning combinations from among the most common strategies, but not necessarily the absolute best combinations. Fifth, the search strategies of firms can hardly be considered exogenous to the firm's innovation performance. We do believe that the fine-grained distinction between strategies only separated with one or two sources makes endogeneity as a source of bias less likely. But we cannot completely rule this out. Finally, by using a systems approach, we have not conducted formal tests of complementarity. Future research should attempt to apply such formal tests when appropriate statistical methods become available. This study suggests several avenues for further research. It would be useful to know whether choosing different combinatorial search strategies influences the degree of novelty or "radicalness" of innovations. It could also map combinatorial search strategies over time to explore how search efforts evolve. This paper has theorized and demonstrated that integrative search strategies combining internal and external knowledge allow the greatest possibility for generation of novel ideas. In doing so, we have advanced the understanding of “winning combinations” of knowledge sources for achieving innovative outcomes, which adds to our understanding of the sources and determinants of innovation.

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Figures and Tables

Figure 1: Distance between the focal firm and sources of knowledge for innovation

Knowledge source / Comparison to focal firm	**Internal**	**Suppliers**	**Customers**	**Competitors**	**Universities**
Economic interests misaligned	By definition, NO	Largely, NO	Largely, NO	Strong potential dangers, YES	Largely, NO
Different incentive system and norms from focal firm	By definition, NO	NO	NO	NO	YES
Cognitive distance to focal firm	Very low	Low	Low	Somewhat high	High

Table 1 Search strategies and descriptive statistics

Variable	ID	#firm	Mean	Std. Dev.
Search Strategies				
No Sources	0	1977	0.29	0.454
Internal sources only	1	164	0.024	0.154
Suppliers only	2	197	0.029	0.168
Customers only	3	147	0.022	0.146
Competitors only	4	25	0.004	0.061
Universities only	5	13	0.002	0.044
Suppliers & Customers	6	206	0.03	0.172
Suppliers & Competitors	7	27	0.004	0.063
Suppliers & Universities	8	12	0.002	0.042
Customers & Competitors	9	122	0.018	0.133
Suppliers, Customers & Competitors	10	273	0.04	0.196
Suppliers, Customers & Universities	11	19	0.003	0.053
Suppliers, Customers, Competitors & Universities	12	34	0.005	0.071
Internal & Suppliers	13	255	0.038	0.19
Internal & Customers	14	218	0.032	0.176
Internal & Competitors	15	23	0.003	0.058
Internal & Universities	16	18	0.003	0.051
Internal, Suppliers & Customers	17	608	0.09	0.286
Internal, Suppliers & Competitors	18	81	0.012	0.109
Internal, Suppliers & Universities	19	35	0.005	0.072
Internal, Customers & Competitors	20	275	0.04	0.197
Internal, Customers & Universities	21	22	0.003	0.057
Internal, Suppliers, Customers & Competitors	22	1255	0.185	0.388
Internal, Suppliers, Customers & Universities	23	104	0.015	0.123
Internal, Suppliers, Competitors & Universities	24	18	0.003	0.051
Internal, Customers, Competitors & Universities	25	38	0.006	0.075
All sources	26	666	0.092	0.29
Dependent and control variables				
Product innovation			0.245	0.43
Process innovation			0.15	0.357
Share of sales from innovative products			7.409	19.356
Firm size (log employees)			4.148	1.492
Firm age			21.725	9.675
R&D active			0.272	0.445
Share of scientists & engineers			5.169	14.44
Part of a group			0.335	0.472
Domestic			0.667	0.471
National Market Focus			0.321	0.467
European Market Focus			0.129	0.335
Beyond Europe Market Focus			0.22	0.414
Innovation co-operation			0.148	0.355
Innovative active			0.654	0.476
Prior innovations			0.203	0.402
Government funding			0.09	0.286

Table 2 Results from the bivariate probit estimations (N=6,792)

	Baseline Model		Full Model	
	Product Innov	Process Innov	Product Innov	Process Innov
Firm size (log employees)	0.004	0.062**	-0.008	0.058**
	(0.014)	(0.015)	(0.014)	(0.015)
Firm age	-0.003	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
R&D active	0.368**	0.230**	0.309**	0.189**
	(0.043)	(0.048)	(0.045)	(0.049)
Share of scientists & engineers	0.004**	0.003*	0.004**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Part of a group	-0.029	-0.069	-0.041	-0.075
	(0.042)	(0.046)	(0.042)	(0.046)
Domestic	-0.092*	-0.024	-0.088*	-0.016
	(0.040)	(0.044)	(0.040)	(0.044)
National market focus	0.068	0.140*	0.063	0.133*
	(0.049)	(0.055)	(0.049)	(0.056)
European market focus	0.255**	0.222**	0.238**	0.209**
	(0.061)	(0.069)	(0.062)	(0.070)
Beyond Europe market focus	0.381**	0.275**	0.359**	0.262**
	(0.056)	(0.064)	(0.057)	(0.065)
Innovation co-operation	0.171**	0.210**	0.146**	0.197**
	(0.049)	(0.053)	(0.050)	(0.054)
Innovative active	0.368**	0.381**	0.287**	0.219**
	(0.047)	(0.054)	(0.053)	(0.062)
Prior innovations	-0.659**	-0.619**	-0.659**	-0.618**
	(0.055)	(0.061)	(0.055)	(0.062)
Government funding	0.306**	0.219**	0.277**	0.183**
	(0.059)	(0.063)	(0.060)	(0.063)
Internal sources only			0.027	0.088
			(0.122)	(0.148)
Suppliers only			-0.112	0.343**
			(0.123)	(0.125)
Customers only			0.034	0.098
			(0.135)	(0.172)
Competitors only			-0.013	-0.156
			(0.344)	(0.454)
Universities only			-0.845	-5.480**
			(0.437)	(0.147)
Suppliers & Customers			-0.07	0.088
			(0.120)	(0.142)
Suppliers & Competitors			0.239	0.694*
			(0.287)	(0.279)
Suppliers & Universities			0.343	0.869*
			(0.401)	(0.374)
Customers & Competitors			0.136	0.364*
			(0.138)	(0.155)
Suppliers, Customers & Competitors			0.095	0.318**
			(0.097)	(0.112)

	Baseline Model		Full Model	
	Product Innov.	Process Innov.	Product Innov.	Process Innov.
Suppliers, Customers & Universities			-0.183	-0.407
			(0.368)	(0.466)
Suppliers, Customers, Competitors, & Universities			0.311	0.687**
			(0.243)	(0.241)
Internal & Suppliers			0.122	0.464**
			(0.102)	(0.110)
Internal & Customers			0.212*	0.414**
			(0.106)	(0.118)
Internal & Competitors			0.262	0.093
			(0.284)	(0.388)
Internal & Universities			-0.453	0.171
			(0.406)	(0.338)
Internal, Suppliers & Customers			0.241**	0.347**
			(0.075)	(0.087)
Internal, Suppliers & Competitors			0.192	0.389*
			(0.163)	(0.188)
Internal, Suppliers & Universities			0.014	-0.178
			(0.239)	(0.265)
Internal, Customers & Competitors			0.303**	0.386**
			(0.097)	(0.109)
Internal, Customers & Universities			0.787**	0.594*
			(0.300)	(0.302)
Internal, Suppliers, Customers & Competitors			0.305**	0.397**
			(0.065)	(0.074)
Internal, Suppliers, Customers & Universities			0.374**	0.681**
			(0.141)	(0.146)
Internal, Suppliers, Competitors & Universities			0.421	0.57
			(0.285)	(0.345)
Internal, Customers, Competitors & Universities			0.547*	-0.083
			(0.235)	(0.257)
All sources			0.285**	0.419**
			(0.074)	(0.084)
Constant	-0.895**	-1.470**	-0.929**	-1.611**
	(0.114)	(0.125)	(0.116)	(0.130)
athrho	0.737**		0.736**	
	(0.031)		(0.031)	
log pseudolikelihood	-5360		-5301	
Wald chi2	1208		9664	

All models include seven 1-digit industry dummies.
Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Table 3 Marginal predicted probability of product and process innovation derived from the bivariate probit estimations

	Marginal Probability of product innovation=1	Marginal Probability of process innovation=1
Firm size (log employees)	-0.002	0.011***
Firm Age	-0.001	0
R&D active	0.089***	0.036***
Share of scientists & engineers	0.001**	0
Part of a group	-0.012	-0.014
Domestic	-0.025*	-0.003
National market focus	0.018	0.025*
European market focus	0.068***	0.040**
Beyond Europe market focus	0.103***	0.050***
Innovation Cooperation	0.042**	0.037***
Innovative active	0.083***	0.042***
Prior innovations	-0.190***	-0.118***
Government Funding	0.080***	0.035**
Internal sources only	0.008	0.017
Suppliers only	-0.032	0.065**
Customers only	0.01	0.019
Competitors only	-0.004	-0.03
Universities only	-0.243	-1.042***
Suppliers & Customers	-0.02	0.017
Suppliers & Competitors	0.069	0.132*
Suppliers & Universities	0.099	0.165*
Customers & Competitors	0.039	0.069*
Suppliers, Customers & Competitors	0.027	0.060**
Suppliers, Customers & Universities	-0.053	-0.077
Suppliers, Customers, Competitors, & Universities	0.089	0.131**
Internal & Suppliers	0.035	0.088***
Internal & Customers	0.061*	0.079***
Internal & Competitors	0.075	0.018
Internal & Universities	-0.13	0.033
Internal, Suppliers & Customers	0.069**	0.066***
Internal, Suppliers & Competitors	0.055	0.074*
Internal, Suppliers & Universities	0.004	-0.034
Internal, Customers & Competitors	0.087**	0.073***
Internal, Customers & Universities	0.226**	0.113*
Internal, Suppliers, Customers & Competitors	0.088***	0.075***
Internal, Suppliers, Customers & Universities	0.107**	0.130***
Internal, Suppliers, Competitors & Universities	0.121	0.108
Internal, Customers, Competitors & Universities	0.157*	-0.016
All sources	0.082***	0.080***

* p<.05; ** p<0.01;*** p<0.001;

Table 4 Results from the Tobit estimations (N=6,792)

	Baseline model	Full model
Firm size (log employees)	-0.889	-1.473*
	(0.726)	(0.725)
Firm age	-0.290**	-0.249*
	(0.102)	(0.101)
R&D active	16.760***	13.380***
	(2.224)	(2.272)
Share of scientists & engineers	0.310***	0.306***
	(0.062)	(0.062)
Part of a group	-1.244	-1.785
	(2.200)	(2.168)
Domestic	-3.585	-3.328
	(2.051)	(2.032)
National market focus	5.598*	5.277
	(2.749)	(2.728)
European market focus	13.731***	12.393***
	(3.209)	(3.206)
Beyond Europe market focus	20.702***	19.310***
	(3.019)	(3.014)
Innovation co-operation	5.891*	5.037*
	(2.452)	(2.446)
Innovation active	20.592***	13.974***
	(2.668)	(2.909)
Prior innovations	-33.697***	-33.331***
	(3.125)	(3.109)
Government funding	16.441***	15.525***
	(2.795)	(2.807)
Internal sources only		3.419
		(6.167)
Suppliers only		-6.929
		(6.321)
Customers only		4.266
		(8.173)
Competitors only		5.340
		(23.320)
Universities only		-36.328
		(21.955)
Suppliers & Customers		2.217
		(6.356)
Suppliers & Competitors		28.366
		(15.528)
Suppliers & Universities		35.613
		(21.778)
Customers & Competitors		8.210
		(7.172)
Suppliers, Customers & Competitors		6.298
		(5.400)
Suppliers, Customers & Universities		-6.859
		(16.891)

Suppliers, Customers, Competitors, & Universities		26.790*
		(12.933)
Internal & Suppliers		14.447**
		(5.287)
	Baseline model	Full model
Internal & Customers		13.856*
		(5.547)
Internal & Competitors		19.384
		(15.189)
Internal & Universities		-23.506
		(15.887)
Internal, Suppliers & Customers		17.246***
		(4.033)
Internal, Suppliers & Competitors		16.768
		(9.291)
Internal, Suppliers & Universities		-7.286
		(9.915)
Internal, Customers & Competitors		20.084***
		(4.697)
Internal, Customers & Universities		8.523
		(11.132)
Internal, Suppliers, Customers & Competitors		19.987***
		(3.502)
Internal, Suppliers, Customers & Universities		18.235**
		(6.498)
Internal, Suppliers, Competitors & Universities		21.926
		(13.191)
Internal, Customers, Competitors & Universities		21.858*
		(9.446)
All sources		17.781***
		(4.004)
Constant	-52.221***	-54.715***
	(5.943)	(6.007)
sigma	54.376***	53.716***
	(1.399)	(1.373)
R-squared	0.0543	0.0581
Log-likelihood	-9529	-9491
Left censored obs	5296	5296
Righ censored obs	77	77

All models include seven 1-digit industry dummies.
Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Table 5 Search strategy comparison matrix for product innovation: two tails *Wald* tests on the coefficients estimates from the bivariate probit model

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1 Internal sources only	0.03	-				*																					
2 Suppliers only	-0.11		-																								
3 Customers only	0.03			-		*																					
4 Competitors only	-0.01				-																						
5 Universities only	-0.84					-																					
6 Suppliers & Customers	-0.07					*	-																				
7 Suppliers & Competitors	0.24					**		-																			
8 Suppliers & Universities	0.34					**			-																		
9 Customers & Competitors	0.14					**				-																	
10 Suppliers, Customers & Competitors	0.09					**					-																
11 Suppliers, Customers & Universities	-0.18											-															
12 Suppliers, Customers, Competitors, & Universities	0.31					**							-														
13 Internal & Suppliers	0.12					**								-													
14 Internal & Customers	0.21		**			**	*								-												
15 Internal & Competitors	0.26					**										-											
16 Internal & Universities	-0.45																-										
17 Internal, Suppliers & Customers	0.24	*	***			**	**										*	-									
18 Internal, Suppliers & Competitors	0.19					**													-								
19 Internal, Suppliers & Universities	0.01					*														-							
20 Internal, Customers & Competitors	0.30	**	***	*		***	***				*						*				-						
21 Internal, Customers & Universities	0.79	**	***	**	*	***	***			**	**	**		**	*		**	*	*	**		-					*
22 Internal, Suppliers, Customers & Competitors	0.30	**	***	**		***	***				**			*			*						-				
23 Internal, Suppliers, Customers & Universities	0.37	**	***	*		***	***				*						**							-			
24 Internal, Suppliers, Competitors & Universities	0.42		*			**											*								-		
25 Internal, Customers, Competitors & Universities	0.55	**	***	**		***	**				*	*		*			**									-	
26 All sources	0.28	**	***	*		***	***				*						*										-

*** $p<0.001$, ** $p<0.01$, * $p<0.05$; coefficient estimates from the bivariate probit reported in the third column. Only shown results of the *Wald* tests when coefficient in the row is greater than coefficient in the column

Table 6 Search strategy comparison matrix for process innovation: two tails *Wald* tests on the coefficients estimates from the bivariate probit model

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1 Internal sources only	0.09					***																					
2 Suppliers only	0.34					***														*							
3 Customers only	0.10					***																					
4 Competitors only	-0.16					***																					
5 Universities only	-5.48																										
6 Suppliers & Customers	0.09					***																					
7 Suppliers & Competitors	0.69	**		*		***	**					**								**						**	
8 Suppliers & Universities	0.87	**		*	*	***	**					**								**						**	
9 Customers & Competitors	0.36					***														*							
10 Suppliers, Customers & Competitors	0.32					***														*							
11 Suppliers, Customers & Universities	-0.41					***																					
12 Suppliers, Customers, Competitors, & Universities	0.69	**		**	*	***	**					**								**						**	
13 Internal & Suppliers	0.46	**		**		***	**					*								**						**	
14 Internal & Customers	0.41	*		*		***	**					*								**						*	
15 Internal & Competitors	0.09					***																					
16 Internal & Universities	0.17					***																					
17 Internal, Suppliers & Customers	0.35	*				***	*													**						*	
18 Internal, Suppliers & Competitors	0.39					***														*							
19 Internal, Suppliers & Universities	-0.18					***																					
20 Internal, Customers & Competitors	0.39	*				***	*					*								**						*	
21 Internal, Customers & Universities	0.59					***						*								**						*	
22 Internal, Suppliers, Customers & Competitors	0.40	**		*		***	**					*								**						*	
23 Internal, Suppliers, Customers & Universities	0.68	***	**	***	*	***	***				**	**						**		***	*		**			***	*
24 Internal, Suppliers, Competitors & Universities	0.57					***						*								*							
25 Internal, Customers, Competitors & Universities	-0.08					***																					
26 All sources	0.42	**		*		***	**					*								**						**	

*** p<0.001, ** p<0.01, * p<0.05; coefficient estimates from the bivariate probit reported in the third column. Only shown results of the *Wald* tests when coefficient in the row is greater than coefficient in the column

Table 7 Search strategy comparison matrix for process innovation: two tails *Wald* tests on the coefficients estimates from the tobit model

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1 Internal sources only	3.42					*																					
2 Suppliers only	-6.93																										
3 Customers only	4.27					*																					
4 Competitors only	5.34																										
5 Universities only	-36.33																										
6 Suppliers & Customers	2.22					*																					
7 Suppliers & Competitors	28.37		**			**											**			**							
8 Suppliers & Universities	35.61		*			**											**			*							
9 Customers & Competitors	8.21		*			*											*										
10 Suppliers, Customers & Competitors	6.30		*			*											*										
11 Suppliers, Customers & Universities	-6.86																										
12 Suppliers, Customers, Competitors, & Universities	26.79	*	**			**	*										**			**							
13 Internal & Suppliers	14.45		***			**	*										**			**							
14 Internal & Customers	13.86		***			**											**			**							
15 Internal & Competitors	19.38					**											**										
16 Internal & Universities	-23.51																										
17 Internal, Suppliers & Customers	17.25	**	***			**	**				**						***			**							
18 Internal, Suppliers & Competitors	16.77		**			**											**			*							
19 Internal, Suppliers & Universities	-7.29																										
20 Internal, Customers & Competitors	20.08	**	***	*		***	***				**						***			***							
21 Internal, Customers & Universities	8.52					*											*										
22 Internal, Suppliers, Customers & Competitors	19.99	***	***	*		***	***				***						***			***							
23 Internal, Suppliers, Customers & Universities	18.24	*	***			**	*										**			**							
24 Internal, Suppliers, Competitors & Universities	21.93		**			**											**			*							
25 Internal, Customers, Competitors & Universities	21.86	*	***			**	*										**			**							
26 All sources	17.78	**	***			**	**				**						***			***							

*** $p<0.001$, ** $p<0.01$, * $p<0.05$; coefficient estimates from tobit model reported in the third column. Only shown results of the *Wald* tests when coefficient in the row is greater than coefficient in the column